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# Assessing the time-sensitive impacts of energy efficiency and flexibility in the US building sector

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Supplementary material for this article is available [online](#)

## Abstract

The building sector consumes 75% of US electricity, offering substantial energy, cost, and CO<sub>2</sub> emissions savings potential. New technologies enable buildings to flexibly manage electric loads across different times of day and season in support of a low-cost, low-carbon electric grid. Assessing the value of such technologies requires an understanding of building electric load variability at a higher temporal resolution than is demonstrated in previous studies of US building efficiency potential. We adapt Scout, an open-access model of US building energy use, to characterize sub-annual variations in baseline building electricity use, costs, and emissions at the national scale. We apply this baseline in time-sensitive analyses of the energy, cost, and CO<sub>2</sub> emissions savings potential of various degrees of energy efficiency and flexibility, finding that efficiency continues to have strong value in a time-sensitive assessment framework while the value of flexibility depends on assumed electricity rates, measure magnitude and duration, and the amount of savings already captured by efficiency.

## 1. Introduction

Residential and commercial buildings consumed 75% of US electricity in 2018 and are expected to drive nearly 70% of projected growth in US electricity demand through 2040 [1]. Buildings thus offer large potential savings in energy, operating costs, and CO<sub>2</sub> emissions for the US electricity sector. Historically, national potential assessments of building efficiency have focused on estimating the annual energy savings delivered by policy instruments such as building codes and standards, equipment labeling, and technology research and development programs [2], with associated estimates of the economic value of energy efficiency reported on an annual basis, as well [3–9]. Such annual potential assessments fundamentally assume that the operational impacts of efficient building technologies remain static across all hours of the day, days of the week, and seasons.

Advances in building technologies enable buildings to play a more active role in managing hourly electric loads to support a low-cost, modernized electric grid

[10, 11]. Smart controls and connectivity give buildings the ability to respond to grid signals and reduce or shift electricity consumption at certain times of day. These reductions and shifts may be achievable while providing comparable levels of core building services such as comfort to occupants, though service level impacts are highly dependent on building envelope and other factors such as occupant and operator preferences [12]. In this paper, we refer to these smart, connected responses as the energy flexibility of a building, which the International Energy Agency defines as ‘the ability to manage its demand and generation according to local climate conditions, user needs and energy network requirements’ [13]. New forms of energy efficiency and flexibility technologies that provide grid services through load shedding and shifting may be an effective option to avoid electric system costs, such as capital costs for new power generation, operation and maintenance costs for existing generation, and capital costs for transmission and distribution upgrades [14–16]. Energy flexible buildings may also support increased penetrations of renewable

energy by reducing the risk of renewable power over-generation and curtailment, thus increasing its cost-effectiveness [17].

Because the cost of supplying electricity varies based on time of day and season [18], grid-focused valuations of building energy efficiency and flexibility must accordingly be assessed at a high temporal resolution. Existing national-scale energy modeling tools have limited ability to characterize the variations in building electricity use across sub-annual time intervals. For example, while the Electricity Market Module of the US Energy Information Administration's (EIA) National Energy Modeling System (NEMS) [19] yields hourly estimates of total US electricity demand, these estimates are not disaggregated to the building sector and its electric end uses, for which NEMS only yields annual estimates.

Moreover, the absence of a consistent framework for assessing the impacts of both energy efficiency and flexibility measures on baseline building electric loads makes it challenging to develop effective strategies for deploying these measures in tandem. Joint assessments of efficiency and flexibility measures are largely absent from the literature on national and regional energy demand, despite the need to understand potential trade-offs and synergies between the two approaches [13]. Recent work places a strong focus on quantifying the flexible potential of buildings at an aggregate level without directly addressing the role of efficiency within the proposed methodologies [20–22]. Studies that do examine both energy efficiency and flexibility either rely on outdated baseline datasets and proprietary forecasts, place a limited focus on peak demand impacts [23], or otherwise afford only qualitative descriptions of the relative impacts of efficiency and flexibility on electricity demand, their possible interactions, and related integration opportunities [24–26].

To address these gaps and limitations, we develop a new basis for quantitatively assessing the time-varying impacts of energy efficiency and flexibility on US building energy use, energy costs, and CO<sub>2</sub> emissions. We map EIA projections of annual baseline building electricity use, cost, and emissions to a sub-annual basis, yielding estimates of hourly, seasonal, and regional variations in building electricity use that support time-sensitive valuation of energy efficiency and flexibility impacts at the national scale. We include an illustrative use of this updated baseline for the case of residential cooling to demonstrate how conventional energy efficiency measures compare to dynamic flexibility measures in terms of their electricity, cost, and emissions savings benefits in US buildings.

To the authors' knowledge, this work is the first to develop a national baseline for time-sensitive valuation of energy efficiency and flexibility in the US building sector. Our analysis framework and results can be used to demonstrate how next-generation building technologies that dynamically reshape energy loads

across the day compare to traditional, static efficiency measures in terms of total energy, cost, and emissions savings potential. In this way, we aim to develop quantitative insights that can inform the emerging debate surrounding demand-side flexibility from buildings as part of energy policy making.

## 2. Methods

Hourly estimates of US building energy use, operating costs, and CO<sub>2</sub> emissions are generated using Scout, v0.4.1 ([scout.energy.gov](https://scout.energy.gov)), an open-source software program<sup>4</sup> developed by the US Department of Energy [27]. Scout estimates the national energy use, CO<sub>2</sub> emissions, and operating cost savings potential of emerging building energy conservation measures (ECMs) across a long time horizon (2015–2050); savings can be explored under multiple technology adoption cases nationally or for a subset of climate zones.

Given that Scout's analysis approach has been described in detail elsewhere [28], we focus on describing the modifications we made to this approach to enable time-sensitive assessments (see appendix B for an overview of Scout's analysis approach and baseline data available online at [stacks.iop.org/ERL/14/124012/mmedia](https://stacks.iop.org/ERL/14/124012/mmedia)). Specifically, we use typical daily energy load, price, and emissions shapes for each season and Scout climate region to re-apportion Scout's baseline annual energy, cost, and emissions totals, which reflect EIA Annual Energy Outlook Reference Case projections [29], across all hours of a year.

Hourly energy load shapes are drawn from the Electric Power Research Institute (EPRI) End Use Load Shapes Library v5.0 [30]. Average hourly energy loads (kW) are normalized by annual electric demand across all hours of a certain day type in peak (May–September) and off-peak (October–April) seasons. Hourly energy loads are also broken out by pre-2004 North American Electric Reliability Corporation (NERC) region [31], facility type (residential or commercial), and energy end use (e.g. lighting, cooling, heating, etc). A selection of the load shapes used is plotted in appendix B (figure B1).

Hourly electricity price shapes correspond to active time-of-use (TOU) rates in the US Utility Rate Database (URDB) [32]. Hourly TOU rates are broken out by customer type (residential, commercial, industrial), month of the year, day type (weekday, weekend), and US Energy Information Administration (EIA) utility code<sup>5</sup>. A selection of the price shapes used is plotted in appendix B (figure B2).

Finally, hourly marginal CO<sub>2</sub> emissions factors are drawn from a previous analysis of these factors for the

<sup>4</sup> Scout's source code is publicly-available: <https://github.com/trynthink/scout>.

<sup>5</sup> Only the residential and commercial TOU rates were used for this study.

US electricity system [33]. Emissions factors are broken out by post-2011 NERC region [31] and by three seasons, summer (May–September), winter (December–February), and intermediate (March–April; October–November). The full set of marginal emissions shapes used are plotted in appendix B (figure B3).

To develop sub-annual estimates of US building energy use, energy cost, and CO<sub>2</sub> emissions, these hourly energy load shapes, price shapes, and emissions factors are translated to a common temporal and spatial resolution and applied to Scout's default baseline data for the sub-annual time segment(s) of interest.

First, a common set of three seasons is established across the datasets: summer (May–September), winter (December–February), and intermediate (March–April; October–November). These seasons match those used in the marginal emissions factor data, requiring modification to the EPRI and URDB datasets<sup>6</sup>.

Given these common seasonal definitions, hourly energy load, electricity price, and CO<sub>2</sub> emissions estimates are mapped to the annual timescale reflected in Scout's baseline data. For energy loads, we estimate the fraction of annual load,  $\Phi_{r,b,u,s,d,h}^{\text{ld}}$ , for each combination of pre-2004 NERC region  $r$ , building type  $b$ , end use  $u$ , season  $s$ , day type  $d$ , and hour  $h$ :<sup>7</sup>

$$\Phi_{r,b,u,s,d,h}^{\text{ld}} = \frac{L_{r,b,u,s,d,h}}{\sum_{s=1}^S \sum_{d=1}^D \gamma_{s,d}^{\text{ld}} \sum_{h=1}^{24} L_{r,b,u,s,d,h}}, \quad (1)$$

where  $L_{r,b,u,s,d,h}$  is the raw hourly load intensity from the EPRI database for pre-2004 NERC region  $r$ , building type  $b$ , end use  $u$ , season  $s$ , day type  $d$ , and hour  $h$ ;  $D$  and  $S$  are the total sets of day types (weekday, weekend) and seasons (summer, winter, intermediate); and  $\gamma_{s,d}^{\text{ld}}$  represents the total number of days per year that fall into day type  $d$  and season type  $s$ , further defined as:

$$\gamma_{s,d}^{\text{ld}} = 52.1429 N_{dw} \frac{N_{ds}}{365}, \quad (2)$$

where the constants 52.1429 and 365 are the number of weeks and days per year, respectively,  $N_{dw}$  is the number of each day type per week (5 for weekdays, 2 for weekends), and  $N_{ds}$  is the number of days that fall under each season (153 in summer, 90 in winter, and 122 in the intermediate seasons).

For TOU electricity prices, we first assess the median and 5th/95th percentile price shapes for a given state  $st$ , building type  $b$ , season  $s$ , and day type  $d$  combination, where the ratio of the maximum to minimum hourly electricity price was used to calculate

percentiles for each combination. Electricity price shapes for each individual utility in the URDB are mapped to a US state by finding the state that is associated with the utility's code in EIA form 861 [34]. Median and 5th/95th percentile electricity price shapes are then normalized by the average annual electricity price, yielding hourly electricity price intensities,  $\Phi_{st,b,s,d,h}^{\text{pr}}$ , for a given combination of state  $st$ , building type  $b$ , season  $s$ , day type  $d$ , and hour  $h$ :<sup>8</sup>

$$\Phi_{st,b,s,d,h}^{\text{pr}} = P_{st,b,s,d,h} \left( \frac{\sum_{s=1}^S \sum_{d=1}^D \gamma_{s,d}^{\text{pr}} \sum_{h=1}^{24} P_{st,b,s,d,h}}{72} \right)^{-1}, \quad (3)$$

where  $P_{st,b,s,d,h}$  is the hourly electricity price from the URDB database for state  $st$ , building type  $b$ , season  $s$ , day type  $d$ , and hour  $h$ , and the parenthesized term represents the average electricity price across all 72 hours covered by our data for a given region and building type (3 seasons, 24 h per season).  $\gamma_{s,d}^{\text{pr}}$  represents the total number of days per year that fall into day type  $d$  and season type  $s$ :

$$\gamma_{s,d}^{\text{pr}} = \frac{N_{dw}}{7} N_{ms}, \quad (4)$$

where the constant 7 is the number of days per week,  $N_{dw}$  is the number of each day type per week, and  $N_{ms}$  is the number of months in each season  $s$ .

For marginal emissions, hourly emissions factors in each season  $s$  are similarly normalized by the average marginal emissions factor across all hours and seasons, yielding hourly marginal emissions intensities,  $\Phi_{rn,s,h}^{\text{mef}}$ , for a given combination of post-2011 NERC region  $rn$ , season  $s$ , and hour  $h$ :<sup>9</sup>

$$\Phi_{rn,s,h}^{\text{mef}} = E_{rn,s,h} \left( \frac{\sum_{s=1}^S \sum_{h=1}^{24} E_{rn,s,h}}{72} \right)^{-1}, \quad (5)$$

where  $E_{rn,s,h}$  is the hourly marginal emissions factor [33] for post-2011 NERC region  $rn$ , season  $s$ , and hour  $h$ , and the parenthetical term represents the average marginal emissions factor across all 72 h covered by our data for a given region.

The hourly annual load fractions ( $\Phi_{r,b,u,s,d,h}^{\text{ld}}$ ) and hourly price and emissions intensities ( $\Phi_{st,b,s,d,h}^{\text{pr}}$  and  $\Phi_{rn,s,h}^{\text{mef}}$ ) calculated above are defined by different regional breakdowns that must be mapped to the American Institute of Architects (AIA) climate zone ( $z$ ) breakdown used in Scout's baseline data. These climate zones, which are specified by number of cooling degree days and heating degree days, have been used historically by the US Department of Energy for its

<sup>6</sup> In the case of the EPRI dataset, it was assumed that the off-peak season (October–April) daily load shapes could be used to represent hourly load intensities for both the winter and intermediate seasons. In the case of the URDB dataset, which breaks down electricity prices on a monthly basis, the average price shapes across all applicable months for each of the three seasons were used.

<sup>7</sup> For example: the fraction (between 0 and 1) of total annual residential cooling load in the MAIN region that occurs on weekdays between 1 and 2 PM across all summer months.

<sup>8</sup> For example: the electricity price on weekdays between 1 and 2 PM for the summer season in commercial buildings in Texas ( $\Phi_{st,b,s,d,h}^{\text{pr}} = 1$  represents an hourly price intensity that is equal to the average electricity price).

<sup>9</sup> For example: the marginal emissions intensity between 1 and 2 PM for the summer season in the ERCOT region ( $\Phi_{rn,s,h}^{\text{mef}} = 1$  represents an hourly marginal emissions intensity that is equal to the average emissions intensity).

Residential Energy Consumption Survey [35]. Pre-2004 NERC region (load shapes), state (price shapes), and post-2011 NERC region (marginal emissions factors) are mapped to AIA climate zone at the county resolution, enabling a population-weighted determination of the portion of each region that falls into each AIA climate zone.<sup>10</sup>

Finally, sub-annual baseline energy, emissions, and cost estimates are calculated by applying the hourly load fractions ( $\Phi_{z,b,u,t,v,y,s,d,h}^{\text{ld}}$ ), price intensities ( $\Phi_{z,b,u,t,v,y,s,d,h}^{\text{pr}}$ ), and emissions intensities ( $\Phi_{z,b,u,t,v,y,s,d,h}^{\text{mef}}$ ) to Scout's annual baseline energy use, CO<sub>2</sub> emissions, and operating cost estimates for the electric fuel ( $f$ ), as defined in (6)–(9):

$$E_{z,b,u,t,v,y,s,d,h}^{\text{base}} = E_{z,b,u,t,v,y,s,d,h}^{\text{base}} \Phi_{z,b,u,t,v,y,s,d,h}^{\text{ld}}, \quad (6)$$

$$E_{z,b,u,t,v,y,s,d,h}^{\text{base-st}} = \frac{E_{z,b,u,t,v,y,s,d,h}^{\text{base}}}{SS_{f=\text{elec},y}}, \quad (7)$$

$$C_{z,b,u,t,v,y,s,d,h}^{\text{base}} = E_{z,b,u,t,v,y,s,d,h}^{\text{base}} CI_{f,y} \Phi_{z,b,u,t,v,y,s,d,h}^{\text{mef}}, \quad (8)$$

$$\psi_{z,b,u,t,v,y,s,d,h}^{\text{base}} = E_{z,b,u,t,v,y,s,d,h}^{\text{base}} FC_{b,y} \Phi_{z,b,u,t,v,y,s,d,h}^{\text{pr}}, \quad (9)$$

where  $E_{z,b,u,t,v,y,s,d,h}^{\text{base}}$ ,  $C_{z,b,u,t,v,y,s,d,h}^{\text{base}}$ , and  $\psi_{z,b,u,t,v,y,s,d,h}^{\text{base}}$  are the total primary energy use, CO<sub>2</sub> emissions, and operating costs attributable to a given baseline stock segment (defined by climate zone  $z$ , building type  $b$ , end use  $u$ , technology  $t$ , and building vintage  $v$ ) in projection year  $y$ , and to a given season  $s$ , day type  $d$ , and hour  $h$  within that projection year.<sup>11</sup>  $SS_{f=\text{elec},y}$  is the site-to-source electricity factor in year  $y$ , which is used to translate primary energy use estimates to the site energy use estimates reported in our results,  $E_{z,b,u,t,v,y,s,d,h}^{\text{base-st}}$ .  $CI_{f,y}$  and  $FC_{b,y}$  are, respectively, the CO<sub>2</sub> emissions intensity for primary energy of baseline fuel type  $f$  in year  $y$  and the primary energy cost for building type  $b$  in year  $y$ . Calculations for site-to-source conversion factors, emissions intensities, and energy costs are further detailed in appendix B.

To calculate the time-sensitive impacts of different energy efficiency and flexibility measures in section 3.3, we define representative Scout ECMs that modify the sub-annual baselines based on percentage reductions to yield new estimates for (6)–(9). These modifications are specific to the type of measure applied (e.g. an efficiency measure applies a percentage load reduction evenly across all hours of the day, while a flexibility measure modifies the baselines based on percentage reductions during peak hours or percentage shifts from peak hours to off-peak hours). Given the variability of TOU rates in the URDB, we calculate savings potential for flexibility measures across a low, medium, and high savings potential, which are characterized

by different measure durations and price intensities from the URDB. Further details are provided in appendix B.

### 3. Results

#### 3.1. Hourly end-use electricity consumption, cost, and emissions totals

We first characterize hourly variations in electricity consumption by building end use in order to identify building loads that are substantial contributors to hourly variations in electricity demand, costs, and emissions. We focus on the residential sector and the year 2018 throughout the following analyses, but the model framework we use can make projections for both residential and commercial buildings for any year from 2015–2050. We include hourly end-use variations in electricity consumption for commercial buildings in 2018, as well as results for the year 2030 for both residential and commercial buildings, in appendix A (figures A1–A3).

Figure 1 presents hourly end-use electricity, cost, and emissions totals for residential buildings in 2018. Figure 1(a) shows that electricity demand peaks from 5 to 6 PM, primarily driven by space cooling, which accounts for over 37% of the total load (excluding miscellaneous loads) during the peak hour. Minimum demand occurs from 3 to 4 AM, when it is 1.7 times lower than at peak. Space heating and water heating are the largest contributors to demand during this hour. Across the day, thermal end uses show the largest temporal variations, whereas other end uses are comparatively flatter.

Figure 1(b) shows the total operating costs of electricity use across each hour, again disaggregated by building end use. This figure shows two cost values for each hour. The labeled totals above each stacked bar represent the cost of each hour's electricity demand under TOU pricing, where the total cost is derived using time-sensitive adjustment factors that weight hourly electricity costs based on an analysis of all existing residential TOU rates from the URDB. Here, we present cost totals using a rate shape that is the 50th percentile of all TOU rates in terms of peak to off-peak price ratio.

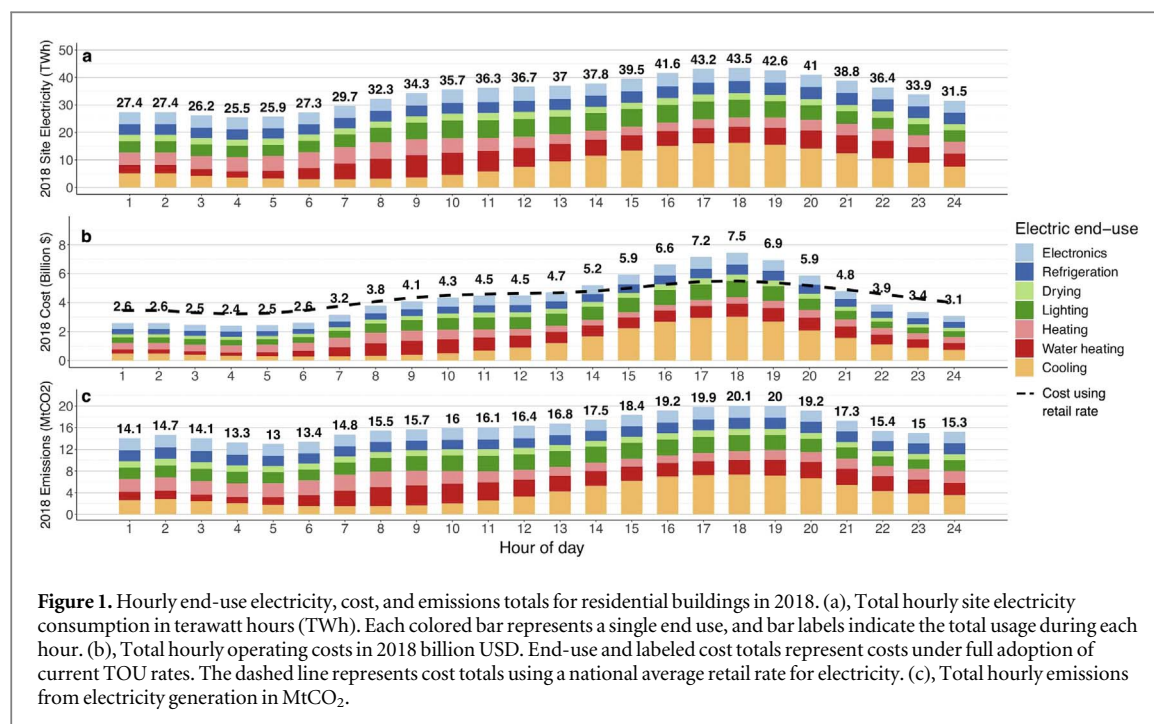
In addition to cost values based on the 50th percentile TOU rate structure, we also present hourly costs using the average residential retail rate for electricity, which was \$0.13/kWh in 2018 [40]. These costs are represented by a dashed line in figure 1(b).

Estimating total costs under TOU pricing amplifies the peak to off-peak ratio seen in figure 1(a), as TOU rates increase during peak hours in order to reflect the higher costs to utilities of supplying electricity during these hours. The total cost during the peak hour is \$7.5 billion, nearly three times higher than during 3–4 AM. Space cooling again accounts for

<sup>10</sup> The database used for this mapping is publicly available [36] and draws from the US Census Bureau [37], the US Environmental Protection Agency's eGRID database [38], and data from the Pacific Northwest National Laboratory used for mapping climate regions to counties [39].

<sup>11</sup> For example: the total primary electricity use attributable to air source heat pump operation in single family homes in northern climates between 1 and 2 PM on summer weekdays in the year 2030.





a substantial share of total costs, around 41% during the peak hour.

Comparing the cost totals under TOU pricing with costs totals under the average retail electricity price shows that full adoption of TOU rates nationally would increase costs by \$8.3 billion between 2 and 8 PM. This represents a 26% increase in electricity costs during the peak period and signals a significant increase in the potential cost savings for measures that reduce electricity use during these hours. Figure 1(b) reveals an opportunity to save electricity costs by shifting peak period electricity use to hours where costs under TOU pricing are below the dashed line (12–8 AM; 9–11 PM).

Total hourly emissions from electricity consumption are shown in figure 1(c). These totals are calculated by applying a marginal emissions scaling factor to each hour's electricity consumption total. The peak to off-peak ratio in marginal emissions, which is around 1.5, is lower than the ratios for either electricity use or costs. This is because marginal power sector emissions are, on average in the US across regions and seasons, slightly higher during nighttime hours than during peak hours. This trend likely occurs because demand is low during nighttime and early-morning hours and coal is more often on the margin. When demand increases during morning and peak hours, gas-fired generators are more often on the margin because they have ramp rates that make them better suited to supplying this demand [33].

### 3.2. Seasonal and regional variations for electric space cooling

Given the large contributions of space cooling to hourly electricity consumption patterns in the

residential sector, next we characterize how electric space cooling and its resulting costs vary seasonally and regionally across the US. We include results for residential space heating in appendix A (figure A4). We present results for seasonal and regional variations in space cooling and heating for commercial buildings there, as well (figures A5–A6).

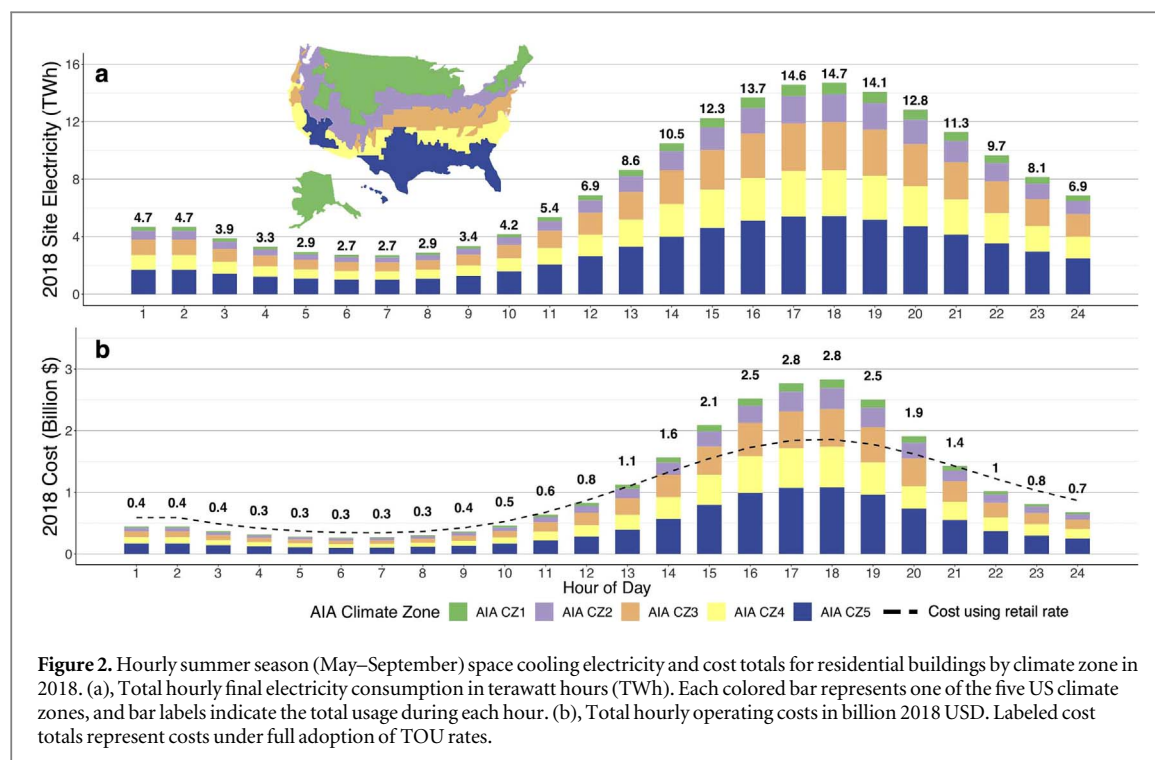
For our analysis of seasonal variations, we split the year into summer (May–September) and winter/shoulder (October–April) seasons. Our regional analysis disaggregates national results to the five AIA climate zones as described in the Methods. The climate zones are ordered numerically from north to south.

As shown in figure 2(a), hourly summer electricity consumption for space cooling during the peak hour (5–6 PM) is five times larger than at its minimum (6–7 AM). Cooling electricity use during peak is concentrated in the southern and mid-Atlantic states, with CZ5 accounting for nearly 37% of demand and CZ3 and CZ4 accounting for an additional 44% during the peak hour.

The hourly cost variations shown in figure 2(b) show an even larger peak to off-peak ratio for space cooling in summer (around 11 times higher during peak). This substantial ramp in hourly cooling costs is due to the alignment of high space cooling loads with the highest TOU prices for electricity during the early evening hours. The total costs for space cooling are again concentrated in climate zones 3–5.

### 3.3. Time-sensitive impacts of efficiency and flexibility measures

The hourly baselines of US building electricity use developed in figures 1 and 2 (and in figures A1–A6) can be used to assess the benefits of conventional



efficiency technologies alongside new flexible building measures in terms of their electricity, cost, and emissions savings potential. We conduct two analyses to demonstrate how these baselines can be used to estimate demand, cost, and emissions impact potentials for residential space cooling measures. We choose residential cooling as an example focus because this end-use segment is both a substantial contributor to US peak electricity demand as well as one that has clear efficiency and flexibility potential [41], but the following analyses could be applied to other major end uses, seasons, and/or the commercial buildings sector.

In the first analysis, we show how national electricity demand and cost savings vary for hypothetical efficiency and flexibility measures with different magnitudes of impact on baseline residential building operations. We include similar estimates of savings potential for commercial cooling measures in appendix A (figures A7 and A8).

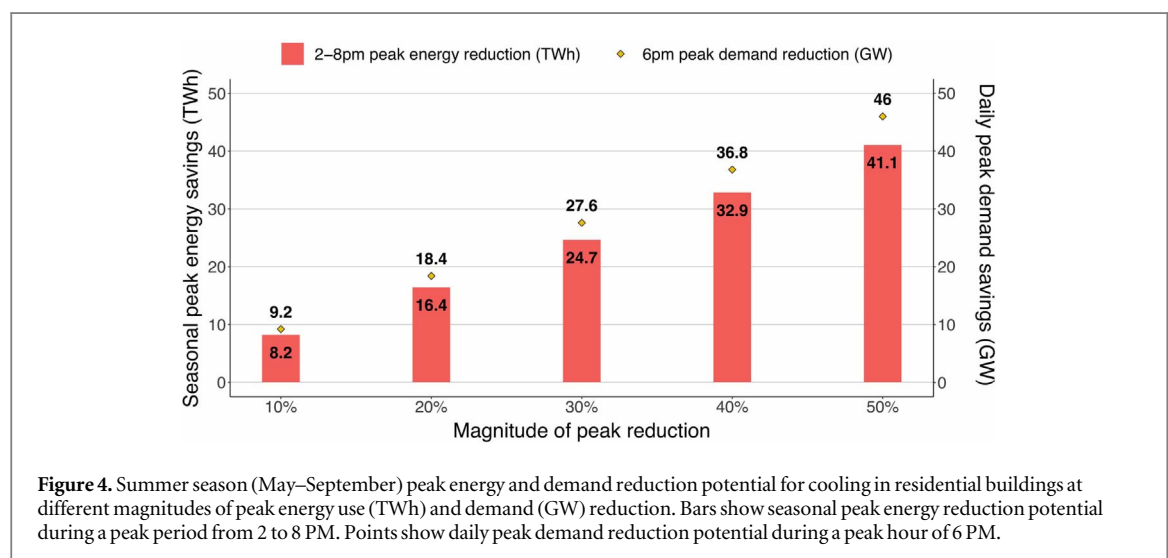
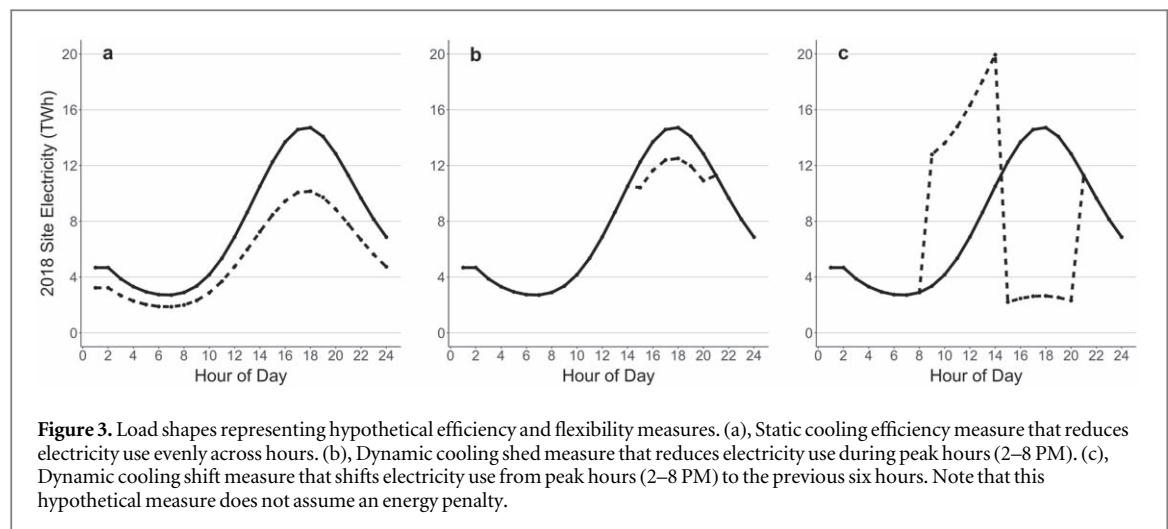
In the second analysis, we demonstrate a more specific application of the sub-annual baselines presented in sections 3.1 and 3.2 by considering example standalone efficiency and flexibility measures with building-level operational impacts that have been reported in previous studies. This analysis is not intended to definitively assess the savings potentials for each measure or for broader portfolios of efficiency and flexibility measures but rather presents an illustrative case of how such measures can be evaluated under a time-sensitive framework. It therefore relies on published point estimates of baseline load impacts, along with simplifying assumptions about building stock envelope efficiency levels, acceptable service thresholds, and occupant behavior; we do not assess the

uncertainty surrounding our estimated demand, cost, and emissions impacts given possible variations in these influencing factors.

Figure 3 illustrates the way the three types of measures we consider can reshape residential space cooling loads. Figure 3(a) shows a hypothetical static cooling efficiency measure, such as an efficient residential HVAC system, that reduces electricity use for space cooling evenly across all hours of the day. In figure 3(b), we represent a measure that sheds electricity use during peak hours (shown in the figure as 2–8 PM). Such a measure would entail, for instance, raising the thermostat cooling set point during this time window. Finally, figure 3(c) shows a second flexibility measure that shifts electricity consumption from peak hours (2–8 PM) to the previous six hours, for example by pre-cooling the building. Note that the shift measure represented in figure 3(c) assumes no net increase in daily energy load—e.g. reductions in peak load are directly translated into load increases of the same magnitude during the previous six hours.

We estimate the savings potential of these measures across varying assumptions about the magnitude of each measure's impact on baseline building operations and underlying TOU rate structures. In figure 4, we present seasonal peak energy savings (TWh) and daily peak demand savings (GW) for the residential sector in summer across different magnitudes of peak reduction, corresponding to figure 3(b). Figure bars show total summer season savings in peak energy use while points indicate average daily peak demand savings, assuming a peak hour of 6 PM. Total seasonal peak energy savings range from 8.2 to 41.1 TWh given a measure that sheds 10%–50% of load during the





hours of 2–8 PM. Daily peak demand savings range from 9.2 to 46 GW, or around 1.2%–5.9% of non-coincident peak summer demand in 2018 [42].

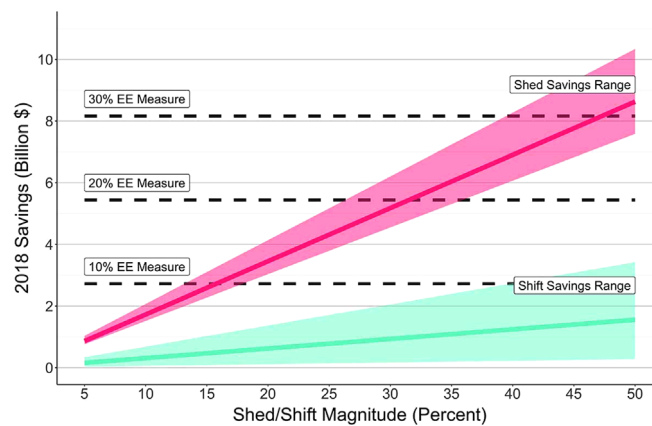
In figure 5, we compare the cost savings potential of the measures represented in figures 3(a)–(c). For the static efficiency measure (figure 3(a)), we calculate cost savings for a 10%, 20%, and 30% reduction in baseline cooling load across all hours of the day. Both the shed (corresponding to figure 3(b)) and shift (figure 3(c)) measures are presented as savings ranges based on the magnitude of peak duration of reduction, assumed reduction, and TOU rate structure. Consistent with figure 3(c), the shift estimates in figure 5 reflect off-peak load increases that match on-peak load decreases —e.g. no additional daily energy penalty is assumed for load shifting. The influence of such penalties on total energy use outcomes is explored later in table 1.

The cost savings for the static efficiency measures in figure 5 total \$2.7, \$5.4, and \$8.2 billion for the 10%, 20%, and 30% load reductions, respectively. Achieving the cost savings of a 10% static efficiency measure using a dynamic measure instead would require a 15% peak reduction under the medium shed scenario

(median rate structure; 2–8 PM peak period) or a 40% load shift under the high shift scenario (95th percentile rate structure; shift from 12–8 PM to 4 AM–12 PM). Similarly, the range in savings potential for a 25% shed measure is \$3.8–\$5.2 billion, which is the same as a static efficiency measure that saves 14%–19% of electricity usage across all hours.

Regarding our analysis of several specific efficiency and flexibility measures, we present seasonal electricity, cost, and emissions savings potentials along with daily peak demand reduction potentials for these measures in table 1. The table includes the technology measures considered along with references for their estimated savings at the individual building level. It also includes assumptions related to measure magnitude and duration as well as the TOU rate structures used.

For the efficiency measure, we model a seasonal energy efficiency ratio 18 cooling system, which can save up to 31% in cooling electricity consumption [43]. For the shed measure, we consider a thermostat set point adjustment, which could be either occupant-led or via direct load control [47]. We assume a 15%



**Figure 5.** Technical cost savings potential for static efficiency and dynamic flexibility measures applied to summer season (May–September) residential cooling loads. Cost savings from static efficiency measures are shown with dashed lines representing three magnitudes of efficiency. The cost savings for both the shed and shift measures are presented as ranges for different magnitudes. The lower bound on the range is calculated using a 4 h shed/shift event and a flatter TOU rate structure (5th percentile of all URDB rates) while the upper bound is calculated using an 8 h shed/shift event and a peakier TOU rate structure (95th percentile of all URDB rates). The solid lines show a 6 h shed/shift event using the median TOU rate structure. We assume no energy penalty for the shift measure in this part of the analysis.

reduction of cooling electricity usage during these hours [44, 45]. We base the shift measure on a previous study [46], which simulates a mechanical pre-cooling measure in a home with thermal performance typical of new construction. We assume a 65% reduction in cooling load during peak hours for this measure and a peak-to-penalty energy ratio of 3.19, defined as the ratio of peak reduction to any *additional* increase in off-peak electricity demand beyond that attributable to pre-cooling. This off-peak load penalty is added on top of the pre-cooling electricity increase, which equals the magnitude of peak electricity reduction (see appendix B.1 for more details on how we translate this measure from the underlying study). Finally, we consider a combined efficiency and flexibility measure, which is based on an efficient cooling system with load shedding capabilities. For the more detailed assumptions on which these measures are based, especially those related to building envelope and service level impacts, we refer readers to the studies cited.

The results show that a static cooling efficiency measure delivers 57.3 TWh of site electricity savings, 29.8 GW of daily peak demand savings, \$8.1 billion in cost savings, and 26.4 MtCO<sub>2</sub> in emission savings. A flexible peak shedding measure, which reduces usage 15% from 4 to 8 PM, yields 8.4 TWh, 14.4 GW, \$1.5 billion, and 3.8 MtCO<sub>2</sub> in savings. A flexible load shifting measure, which shifts 65% of the 4–8 PM load to the previous four hours via pre-cooling, leads to an overall increase in electricity use, costs, and CO<sub>2</sub> emissions but results in much larger daily peak demand savings (62.4 GW) than the other measures. A combined smart-controlled, high-efficiency HVAC system yields the largest electricity, cost, and emissions savings across these three metrics, totaling 63.1 TWh, \$9.2 billion, and 29.1 MtCO<sub>2</sub>, though these savings are

less than the sum of the efficiency and peak shedding measures when considered separately. This measure also delivers 39.8 GW of daily peak demand savings, the second highest magnitude of peak demand reduction after the pre-cooling shift measure.

#### 4. Discussion

Examined across the summer season, the total electricity, cost, and emissions savings impacts of the peak shed and shift measures in table 1 appear less favorable than those of installing more efficient cooling systems in residential buildings. Indeed, efficiency measures continue to have high value in a time-sensitive framework, as efficient cooling also delivers substantial reductions in peak demand. In the case of load shifting through pre-cooling, a slight increase in seasonal electricity use (around 6% of the total), costs, and emissions is observed, reflecting the influence of the off-peak energy penalty assumed for this measure. Nevertheless, this measure also yields the highest daily peak reductions, demonstrating how the benefits of these dynamic measures are variable under a time-sensitive framework depending on which time period is chosen for measure assessment. Moreover, figure 5 shows that the cost implications of shed and shift measures depend heavily on the assumed magnitude and duration of peak savings for such measures, as well as assumed time-varying electricity rate structures. While the TOU rate shapes applied in this paper reflect current offerings from utilities, future rate structures may more heavily reward mid-day load increases [48], in which case pre-cooling measures would yield greater cost savings. Finally, while cost effectiveness was not the focus of the current analysis, measures that shed or shift loads may require lower incremental capital costs and thus deliver electricity savings more

**Table 1.** Assessment of specific seasonal (May–September) cooling efficiency and flexibility measures under a time-sensitive framework to estimate their national electricity, cost, and CO<sub>2</sub> emissions savings potential in residential buildings in 2018.

Savings measure	Example technology	Assumptions	Estimated seasonal electricity savings (TWh)	Estimated daily peak demand savings (GW)	Estimated seasonal cost savings (Billion USD)	Estimated seasonal emissions savings (MtCO <sub>2</sub> )
Static cooling efficiency improvement	SEER 18 cooling system [43]	31% savings, all hours; median TOU rate structure	57.3 <sup>a</sup>	29.8	\$8.1	26.4
Flexible cooling, peak shed	Thermostat set-point adjustment [44, 45]	15% reduction, 4–8PM; median TOU rate structure	8.4	14.4	\$1.5	3.8
Flexible cooling, peak shift	Thermal storage with pre-cooling [46]	65% shift from 4–8PM to 4 hours earlier; 1.7 °C thermostat turn-down; 3.19 peak-to-penalty ratio; median TOU rate structure	−11.4	62.4	−\$0.6	−5.5
Combined efficiency and flexibility measure	SEER 18 cooling system with smart-controlled load shedding capability	31% savings, all hours, plus 15% reduction, 4–8PM; median TOU rate structure	63.1	39.8	\$9.2	29.1

<sup>a</sup> Reference totals for summer season residential cooling in 2018 are 184.8 TWh, 96.2 GW, \$26.2 billion USD, and 85.2 MtCO<sub>2</sub>.

cost-effectively than conventional efficiency measures when paired with time-varying electricity rates [15].

The results presented in table 1 are primarily intended to show how the time-sensitive framework developed in this paper can be used to quantify the hourly and seasonal load, cost, and emissions impacts of specific efficiency and flexibility measures. As mentioned, we rely on point estimates of each measure's building-level operational impacts from previous studies, and a full uncertainty analysis of these estimates is beyond the scope of this paper. Nevertheless, we acknowledge the importance of undertaking more detailed analyses of measure operation at the building-level, especially regarding the uncertainties inherent to measure performance in different building and climate contexts, as well as those related to a measure's expected service level impacts and the degree to which changes in building services would be accepted by building operators and occupants. Furthermore, we note that the full savings potentials estimated for the flexibility measures in table 1 may not be realized when these measures are implemented in practice, as utilities will adjust the timing of load shifts and recovery periods to avoid creating new peaks in the system load shape.

Direct comparison of our findings with previous studies of US building efficiency and flexibility impacts on hourly electric demand is precluded by the narrow focus in these studies on maximum peak demand reductions for a specific set of technology and program deployment scenarios. For example, a study of national efficiency and demand response (DR) potential by EPRI [23] estimates 218 GW of summer peak reduction from efficiency and DR measures by 2030, with 12.5 GW attributable to direct residential central air-conditioning control by utilities. A 2009 Federal Energy Regulatory Commission study [49] estimates 188 GW of summer peak reduction potential from DR alone in 2019 but includes the industrial sector in this estimate. Another study of demand-side flexibility by the Rocky Mountain Institute (RMI) [15] finds 49 GW of summer peak reduction potential from shedding 25% of residential air-conditioning loads in 2014. In all cases, the focus on maximum daily summer peak contrasts with our estimation of average daily summer peak; thus, the estimated impact on peak demand from a 25% residential cooling reduction in our study (about 25 GW, figure 4) is smaller than that of the RMI study, for example. Moreover, these studies rely on datasets that are by now more than a decade old. Broadly speaking, however, the large potential these studies suggest for peak electric demand reductions from the building sector, and the prominent role of efficiency in these reductions in the EPRI study, are supported by our results.

The valuation approach presented in this paper is based on utility TOU rates for residential and commercial customers, assuming that such rates constitute a reasonable, readily-available proxy for the actual

time-varying costs to utilities for supplying energy.<sup>12</sup> Future work could incorporate more direct proxies for the time-varying costs of electricity supply, such as wholesale locational marginal pricing (LMP), into our time-sensitive valuation framework. This research should consider how different valuation approaches might adjust the estimated savings potential of efficiency and flexibility measures, especially under high-renewable energy penetration scenarios, which are expected to reshape temporal variations in LMP considerably [48].

Similarly, the data used to apportion annual electricity end uses and emissions estimates to a sub-annual basis (see section 2) will continue to be updated. Regarding sub-annual electric load data, reference models of whole building energy use from the US Department of Energy have recently been used to generate highly granular estimates of hourly energy demand across all major end uses, building types, and for all 8760 hours of a typical meteorological year [50]. A related effort at the US national labs is generating hourly load profiles for thousands of prototypical buildings and calibrating these profiles against metered utility data [51]. Regarding sub-annual emissions data, hourly marginal emissions intensities based on the US Environmental Protection Agency's Continuous Emissions Monitoring System continue to be updated by the Carnegie Mellon Center for Climate and Energy Decision Making and made publicly available via an online repository [52].

Future work will also focus on developing more specific definitions of energy flexibility measures, their impacts on building operations, and their cost effectiveness. While hourly load shape measurements for individual building technologies remain scarce, regionally-focused measurement efforts (e.g. [53]) provide a basis for developing and validating measure load savings shapes, which can be extended to regions without readily available savings shape measurements using whole building energy simulation programs [54]. In developing such saving shapes, service level thresholds should be considered explicitly—at minimum by referring to relevant operational standards such as ASHRAE Standard 55 and 62 for thermal comfort and ventilation, respectively, and the IES Lighting Handbook for task illumination [55–57]. Once developed and validated, measure savings shapes can be paired in Scout with associated data on technology capital costs and the latest estimates of time-varying electricity prices to explore the cost-effectiveness of flexibility measures alongside that of conventional efficiency measures. Taken together, these updates to the modeling framework and its underlying data ensure that the current analysis is repeatable and that it remains relevant to policy questions concerning the

<sup>12</sup> Time-varying demand charges are also cataloged in the URDB and could similarly be used as a readily available utility cost proxy for time-sensitive efficiency valuation.

role of building energy efficiency and flexibility in enabling a low-cost, low-carbon US electricity system.

## 5. Conclusions

This paper develops hourly estimates of US building electricity use, cost, and CO<sub>2</sub> emissions in order to facilitate the analysis of electricity saving measures with time-sensitive impacts alongside conventional, static efficiency measures. The national savings potentials for static energy efficiency measures and dynamic flexibility measures presented here enable a like-for-like comparison of next-generation building technologies that dynamically reshape energy loads with traditional efficiency technologies. Quantifying the magnitude of these measures' time-sensitive impacts across multiple metrics is critical to positioning the buildings sector as a key source of demand-side flexibility in a future that is likely to see increased stress on the power grid from climate change as well as higher penetrations of variable renewable energy generation [17, 58]. Moreover, from a consumer perspective, a move towards electricity pricing that better reflects the real time-varying cost of energy supply will mean that reductions in electric load during peak demand hours deliver larger cost savings than reductions during off-peak hours, increasing the attractiveness of measures that yield impacts during high-price periods. An analysis framework that accounts for this time-varying value is essential for determining the cost effectiveness of large-scale energy efficiency or flexibility technology adoption in the building sector under the rate structures that are likely to emerge in a future US electricity system that relies more heavily on distributed energy resources [59, 60].

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## Data availability

The data that support the findings of this study are openly available at DOI:<https://doi.org/10.5281/zenodo.3473478>.

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